

## ■ STUDIES ■

Borbála Szüle

# *Systemic Risk Dimensions in the Hungarian Banking and Insurance Sector*

**SUMMARY:** The consecutive financial crises have made the analysis of the systemic risks of financial institutions increasingly important worldwide. The researches so far have been primarily focusing on the banking sector, but insurance companies have also been given an increasing attention. Based on past literature, systematic risk can be measured in a variety of ways, and one of the options is the calculation of the indicators typical of return comovement. This study compares the dimensions calculated by the multidimensional scaling of returns in the banking and insurance sector. The results suggest that return dimensions in the Hungarian banking and insurance sector (related to systemic risk) are not completely independent, and, compared to the banking sector, the return comovement related systemic risk is lower in the insurance sector.<sup>1</sup>

**KEYWORDS:** bank, insurance, systemic risk

**JEL CODES:** G21, G22

The objective of this study is to contribute to the extensive literature on systemic risk by analysing the Hungarian banking and insurance data. Systemic risk has a variety of definitions (Eling-Pankoke, 2014), the scope of the indicators is, therefore, very wide (Giglio et al., 2016; Ellis et al., 2014; Eling-Pankoke, 2014; Kleinow et al., 2017; Sedunov, 2016). According to the definition used in the study (similarly to the approach described by Billio et al., 2010), the point of systemic risk is the similarity of different institutions, which can be measured by a principal component analysis. *Kritzman et al.* (2011) call the systemic risk indicator calculated based on the result of the principal component analysis absorption ratio.

The absorption ratio is defined by Kritzman et al. (2011) as the indicator of what part of the total variance of a given set of assets is accounted for ('absorbed') by some eigenvectors. Kritzman et al. (2011) determine that the greater value of the absorption ratio corresponds to a higher level of systemic risk, because in this case the sources of the risk are more uniform. In this study we compare the banking and insurance systemic risks based on indicators similar to this absorption ratio. This indicator measures the effect of structural and cyclical systemic risks, also distinguished by the MNB (2018a), together, but based on the related calculations, it might theoretically be possible to separate the two types of systemic risk.

In this study, we use the method of multidimensional scaling instead of the principal component analysis belonging to the absorp-

---

*E-mail address:* borbala.szule@uni-corvinus.hu

tion ratio. The reason for this is that from a methodological aspect multidimensional scaling is more adequate in the case of the available data. In the case of the Hungarian banking and insurance sector, no stock-market data are available on daily returns covering most of the sectors; return data concerning the sectors as a whole can only be calculated from accounting balance sheet and profit and loss statement data, the number thereof is, however, not sufficient to appropriately carry out the principal component analysis. However, the results of multidimensional scaling and principal component analysis are sometimes, theoretically, the same (Bécavin et al., 2011); the results of the two methods can be directly produced from each other if certain conditions are met (Kovács, 2014; 226.). On this basis, we use the interval measurement model of multidimensional scaling in this study, where, similarly to the principal component analysis, eigenvectors can also be calculated, which can be interpreted as return dimensions in this analysis.

The analysis strives to take into account the data of the banking and insurance sector as fully as possible, so the analysis is founded on the available data of the banking and insurance balance sheets and profit and loss statements between 2003 and 2015 (downloadable from the website of the Magyar Nemzeti Bank). The analysis includes the data of 16 banks and 17 insurance corporations (institutions in the case of which there were data available for the entire period covered by the analysis, and the average return on equity was not a negative value). In 2015, within the consolidated balance sheet total the total amount of the balance sheet totals of the institutions included in the analysis amounted to 63.22 percent in the banking sector and 79.44 percent in the insurance sector.

The study primarily would like to contribute to the literature by comparing the Hungarian banking and insurance systemic risk

(measured based on the similarity of the return dimensions), in which literature it is still relatively rare to compare the two sectors from a systemic risk aspect. The analysis of insurance activity separately from the banks is becoming more and more important nowadays, as the activity of the non-bank financial intermediaries can lead to the growth of systemic risks as a result of a variety of impacts (MNB, 2018b), partly because (based on empirical results) a causal relationship can be assumed between insurance activity and economic growth (Arena, 2008). The comparison of the insurance and banking sector may mean interesting results for the macroprudential supervision as well, since, theoretically, the macroprudential policy tools affecting the whole financial intermediary system primarily affect the banking sector in practice (Kálmán, 2016), and they deal with the expansion possibilities of the macroprudential regulatory framework system of insurance corporations at both global and European level (MNB, 2018b).

When comparing the two sectors, in addition to using the Hungarian data, the study also analyses the value of correlations between the return dimensions, which is also still not frequent; the results calculated with Hungarian data can be considered as a novelty in the literature.

The next, 2<sup>nd</sup> part of the study provides an overview of the systemic risk indicators commonly mentioned in the literature. The 3<sup>rd</sup> part is about the comparison of the banking and insurance systemic risk, and the 4<sup>th</sup> part contains the new empirical results of the study. The conclusions of the study are summarised in the 5<sup>th</sup> part.

## THE MEASUREMENT OF SYSTEMIC RISK

Financial stability is important for the entire economy, but it does not have a uniformly used definition in the literature, it is more

common to define financial instability (Baur, Schulze, 2009). Systemic risk is an associated concept, but it does not have a uniformly used definition in the literature either (Eling, Pankoke, 2014). In the case of definitions, it is theoretically easy to distinguish, for example, the term of risk (which can be analysed by statistical methods) and uncertainty (which cannot be identified by statistical methods) (Medvegyev, 2011), but risk is a term which cannot be directly measured (latent) in a statistical sense (Kovács, 2011), so practically, we can strive to measure the different aspects of risk at best. It is also typical in the case of systemic risk, the complexity of which is shown by the fact that in Europe, based on certain data, even its connection with the return on sovereign debt can be demonstrated (Pagano, Sedunov, 2016).

In the measurement of systemic risk a macro and a micro approach can be distinguished: the macroprudential indicators assess systemic risk at the level of the entire economy, while the microprudential indicators can be quantified in relation to each institution (Eling, Pankoke, 2014). In the European Union it is the European Systemic Risk Board that fulfils the macroprudential financial supervision, and the European supervisory authorities are responsible for the microprudential supervision (Szegedi, 2012). In their study *de Bandt and Hartmann* (2000) distinguish the horizontal aspect of systemic risk, within which the analysis only focuses on the financial sector, and the vertical aspect, which takes into consideration the impact on the economic output as well in the analysis of systemic risk. In the case of systemic risk, furthermore, we can distinguish cyclical and structural systemic risks: the source of cyclical systemic risk is the willingness to take risks, which is comoving but also differing from the optimum level in a certain direction, while structural systemic risk corresponds to the structure of the

network between the different financial players (MNB, 2018a). Theoretically, financial stability risks can also be reduced with monetary policy and macroprudential policy tools, the prevention of the emergence of a system-level crisis can be considered as the primary task of macroprudential policy (Fáykiss, Szombati, 2013). Prior to the financial crises, the cyclical changes of systemic risk is shown, for example, by the rate of total debts compared to the GDP („*Basel gap*”) (Lang et al., 2019), and the risks arising from the features of the banking networks can be calculated in different ways (for example Lublóy, 2005). In alignment with the different types of systemic risk the macroprudential tools include the countercyclical capital buffer as well as the structural systemic risk buffer (Kálmán, 2016).

According to the empirical results of *Weiß et al.* (2014) the global systemic risk is primarily influenced by the characteristics of the supervisory system, and the permanent impact of certain characteristics of the banks (for example, their credit portfolio quality) is not justified by the empirical results. In the European Union the European Systemic Risk Board (ESRB) was established in 2010, and its objectives include the prevention and mitigation of systemic risk. The banking sector of several European countries has systemic risk capital buffer (*systemic risk buffer*) in order to mitigate systemic risks. The International Association of Insurance Supervisors (IAIS) also deals with the development of the activity-based evaluation methods of systemic risks in the insurance sector (ECB, 2017;133.). *Gauthier et al.* (2012) carried out calculations based on the data of Canadian banks in order to find out what impacts the application of systemic risk based macroprudential capital requirement might have on the banking sector. They defined macroprudential capital requirement as a fix point, in the case of which the capital requirement of each bank conforms to their con-

tribution of the risk of the entire system (in the case of the recommended capital requirement). On the basis of their empirical results, the application of this systemic risk-based capital requirement reduced the likelihood of individual bank failure as well as the likelihood of a system-level crisis by approximately 25 percent. This result was calculated by Gauthier et al. (2012) by a network-based structural model. The network-based modelling approach has spread in the systemic risk literature over the last years (for example de Souza et al., 2016; Huang et al., 2016; Hu et al., 2015; Balog et al., 2012; Csóka and Kiss, 2015). Such expansion of the literature allows a more precise modelling of systemic risk, since the representative banking hypothesis used in the traditional theoretical approach about bank regulation does not take into consideration, among other things, that in the general equilibrium the investment decision of each bank can theoretically have an external impact on the results of the other banks, thus, also on their investment decisions (Acharya, 2009).

The variety of the impacts of financial institutions exercised on each other also contributes to the fact that the range of systemic risk indicators is extremely wide. *Eling and Pankoke* (2014) identified three important definition elements following the review of the 26 definitions of systemic risk:

- the occurrence of some event (for example, the bankruptcy of the financial institution, the development of a shock affecting the economy as a whole, etc.);
- the impact of the event (most of the definitions determine the consequences of the occurrence of the event, for example, that the event adversely influences the real economy);
- causal connection (some definitions highlight the causal connection, when it considers a given risk as systemic risk).

In connection with the banking system-

ic risk *de Souza et al.* (2016) identified some channels through which the risks may spread between the institutions:

- risk concentration channel, when a large part of the banks are exposed to a common risk factor,
- contagion channel through balance sheet,
- contagion transmitted by the prices, for example, when an asset needs to be sold quickly („*asset fire sales*”),
- the development of illiquidity spirals.

The range of systemic risk indicators is very wide: indicators which can be defined in many different ways have spread in the theoretical model construction, and several different indicators have spread in the practical calculations, too. *Giglio et al.* (2016) classifies a couple of systemic risk indicators applied more commonly in the following groups:

- indicators measuring institution specific risk, which measure the contribution or sensitivity of an institution towards the systemic risk measured at the level of the overall economy; they include, for example, the  $\Delta\text{CoVaR}$  defined by *Adrian and Brunnermeier* (2008), which is the difference of the conditional (financial) system-level VaRs measured by assuming the financial institution to be in a distressed state and to be in a median state;
- indicators with comovement and contagion focus, which measure the connection between the share returns of financial institutions, including, for example, the absorption ratio also mentioned by *Kritzman et al.* (2011), which measures what proportion from the variance of the financial system is accounted for by the first few principal components;
- volatility and instability indicators (which can, for example, be calculated from the average of the share volatility of the financial institution);
- liquidity and credit indicators;

- other indicators (for example, the indicators associated with the relationships between financial institutions, the values relating to the inter-bank credits, etc.).

The cumbersomeness of the grouping of systemic risk indicators is shown by the fact that numerous indicators do not fit well the four categories (apart from the ‘miscellaneous’ category) presented by *Giglio et al.* (2016); the indicator applied by *Huang et al.* (2009) can be considered as such a category, which measures systemic risk by the theoretical price of the insurance against financial difficulties (a kind of risk-based deposit insurance). Overall, it can be stated that the different aspects of systemic risk are not easy to separate even theoretically. *Raffestin* (2014) stated, for example, that portfolio diversification (for example in the assets of a bank) may, on the one hand, mean greater individual security, on the other hand, relationships are established between the investors by holding identical assets, which results in the formation of a kind of ‘endogenous covariance’ and also contributes to the systemic risk.

The covariance and correlation between returns is given an important role in the literature about systemic risk measurement. In his theoretical model *Acharya* (2009) measures systemic risk by the value of the correlation relating to the returns of the assets held by the banks, selected in an endogenous manner. In his theoretical model, by analysing the choice of portfolio by the banks, *Wagner* (2009) presents that when the external impacts of bank failure depend on the overall condition of the banking sector, a lower correlation at the banks is not necessarily more advantageous from the aspect of the financial system as a whole.

The systemic risk indicators measuring the comovement of returns have also spread in practical calculations. *Civitarese* (2016) primarily deals with characteristics of the absorption ratio, eigenvalue entropy and Index

Cohesion Force from the few systemic risk indicators based on return correlations:

- Index Cohesion Force is the ratio of the average correlation calculated based on daily returns and the average partial correlation (the index calculates by filtering the impact of returns);
- the absorption ratio also described by *Kritzman et al.* (2011) can be calculated by the eigenvalue-eigenvector decomposition of the covariance matrix of the returns, and can be interpreted as total variance proportion explained by high eigenvalues;
- eigenvalue entropy can be calculated on the basis of the eigenvalue-eigenvector (or singular value) decomposition of the correlation matrix.

## THE SYSTEMIC RISK DIFFERENCES OF FINANCIAL SECTORS

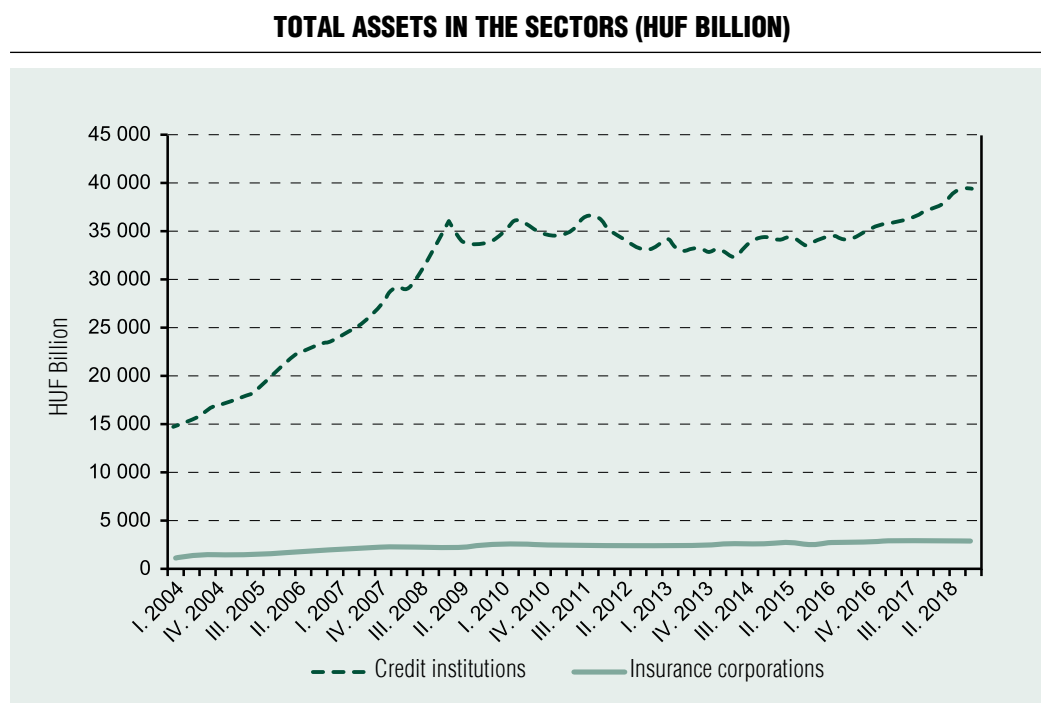
The traditional players of the financial intermediary system are the (commercial) banks, one of the principal activities of which is the acceptance of deposits and lending. An important source of the risks typical of the functioning is that the maturity of the deposits is usually shorter than that of the loans. The problems of each bank may constitute a system-level risk, as the financial problems of the banks interlinked through the network of mutual payments, among other things, may spread to other banks, too. New sources of systemic risk developed by the spreading of modern financial services; for example, by the development of financial groups, theoretically, even the financial problems of insurance companies may spread to the banking sector. The rate of systemic risk is, however, not necessarily identical in the different sectors; the rate of systemic risk may be influenced by the size of the given sectors. In Hungary, the assets calculated from

the consolidated balance sheet of credit institutions at the end of the third quarter of 2018 was approximately 13.8 times the total assets included in the statistical balance sheet of the insurance companies. *Figure 1* shows the temporal evolution of these two values

It is clear from *Figure 1* that the systemic risk effect of the insurance companies in the Hungarian financial sector may currently be lower, partly as a result of the size of the sector, compared to the banking sector; however, this statement can be phrased more precisely based on each institutional data. In the case of the differences in the sizes of each sector, it must also be considered that the size proportions may change in the longer term: at the same time (at the end of the third quarter of 2018) in some countries of the European Union the ratio of the assets of credit institu-

tions and insurance corporations had variable values, as shown by *Figure 2*. The indicators which can be interpreted similarly to the Hungarian data (which is approximately 13.8) include values over 20 as well as values below 3. The lowest value was 1.76 in Ireland, and the French (2.95), Belgian (3.15) and German (3.5) values are also relatively low. The relative size of the insurance and banking sector may be influenced by many factors, for example, the consumption of life insurance products may correspond to cultural factors (Chui, Kwok, 2008), and according to an empirical analysis the most robust explanatory factors of the use of life insurances include, for example, the development level of the banking sector, inflation and income per capita (Beck, Webb, 2003). As the economy develops and insurance products spread, the ratio of the in-

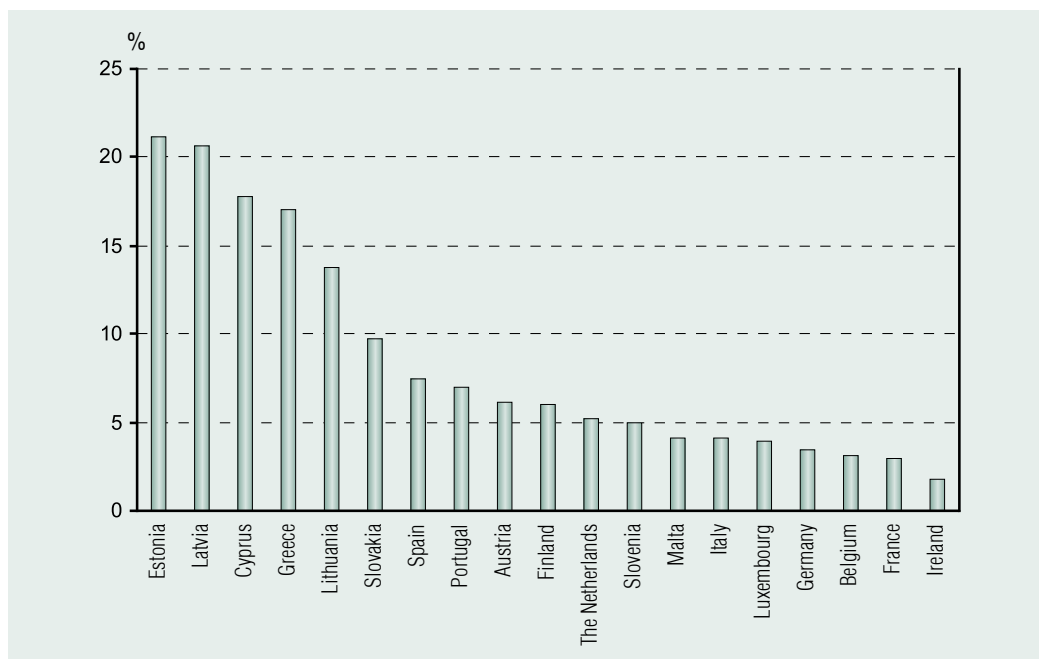
Figure 1



Source: [www.mnb.hu/statisztika/statisztikai-adatok-informaciok/adatok-idosorok/x-monetaris-es-egyeb-merlegstatisztikak](http://www.mnb.hu/statisztika/statisztikai-adatok-informaciok/adatok-idosorok/x-monetaris-es-egyeb-merlegstatisztikak)

Figure 2

**RATIO OF THE ASSETS OF CREDIT INSTITUTIONS AND INSURANCE CORPORATIONS**



Source: European Central Bank, <http://sdw.ecb.europa.eu/> and own calculations

insurance sector measured in comparison with the banking sector may increase in Hungary, which also supports the importance of systemic risk researches conducted in the insurance sector.

When comparing the financial sectors, it is important to precisely define the systemic risk indicator. In the comparison of the systemic risks of the banking and insurance sector the past literature often focused on the potential impacts of the ‘infections’. This is an important direction for the researches, and in this respect the literature often includes the statement that the systemic risk of the traditional insurance activity is lower compared to the activity of the banks (Kessler, 2013; Trichet, 2005; Eling-Pankoke, 2014). One of the main related theoretical arguments is that in the case of insurance corporations, there is not

as high a level of institutional interconnection as the one observed in the inter-bank market and in the operation of the payment system (Thimann, 2014). The systemic risk of banks can be largely influenced by the inter-bank network of relationships, the maturity transformation combined with leverage, the presence of liquidity risk and the operation of the payment system (Thimann, 2014). These factors are not typical in the traditional insurance market, so it can be assumed that the systemic risk of insurance corporations differs from that of the banks.

The spreading of the ‘infections’ corresponding to the institutional insolvency through the relationships between insurance corporations and reinsurance corporations could theoretically be possible by reinsurance (Morrison, 2003); however, the insolvency of



a reinsurance corporation is not likely to have sector-level impacts in particular, but rather institutional impacts (ESRB, 2015). Based on the ESRB (2015, p. 14–17), the systemic risk impact of insurance corporations (on the financial system or the real economy) may arise from the participation in non-traditional, non-insurance activities (for example, the undertaking of certain types of guarantee), from the procyclicality potentially appearing in asset allocation, from the procyclicality observed in the rate setting of insurances and, for example, from the combined exposure to interest rate risk.

Compared to the banking sector, there is also a difference in terms of the emergence of institutional insolvency in the insurance sector (and in any potential ‘infectious’ impacts thereof), since the clients of the banks can, in theory, immediately take out the fixed-term deposits from the bank, while in the case of insurances, the procedure of repurchases relating to contracts, with similar effect may be much slower, and the administrative costs associated with the procedure might hold back the customers from repurchasing the contracts (Morrison, 2003). The practical experience relating to financial crises suggest that the measurement of systemic risk is important in the case of the insurance sector as well (Arnold et al., 2012); the IAIS (International Association of Insurance Supervisors) also deals with the possibilities of the activity-based evaluation of systemic risk in the case of insurance corporations (ECB, 2017, p. 133).

The empirical results relating to the topic do not clearly demonstrate the lower systemic risk of the insurance sector, the comparison of the (precisely defined) components of the insurance and banking systemic risk can, therefore, be seen as a current issue. When comparing the  $\Delta\text{CoVaR}$  (Adrian, Brunnermeier, 2008) type systemic risk indicators of the banking sector, the insurance sector and oth-

er financial services sector, *Bernal et al.* (2014) determined that all the three financial sectors significantly contributed to systemic risk in the case of both the euro zone and the USA. By using data from between 2004 and 2012 for the analysis, Bernal et al. (2014) also found that in the euro zone the other financial services sector and the banking sector made a larger systemic risk contribution than the insurance sector, while in the case of the USA, the insurance sector made the largest systemic risk contribution in the same period.

## METHODOLOGICAL OVERVIEW AND EMPIRICAL RESULTS

The literature of systemic risk mentions numerous different indicators, and from the different approaches an outstanding number of indicators are linked to network theory and return comovement. These two measurement approaches can be considered to be the same from a certain point of view, as, theoretically, network theory may contribute to the explanation of return comovements. In the next part, though, we will not discuss the theoretical differences between the two types of measurement approaches, but we will only interpret the results of the calculations carried out similarly to one of the selected indicators. This selected indicator is the absorption ratio, which, based on Kritzman et al. (2011), can be determined by taking into account the eigenvalues calculated as the result of a principal component analysis. In mathematics, for example, eigenvalues can be interpreted in connection with the spectral decomposition theorem of symmetrical matrix, if, for example, there is a symmetrical matrix  $M$ , then, based on the spectral decomposition theorem, there is an orthonormal base belonging to matrix  $M$  (which contains the eigenvectors of matrix  $M$ ), in which matrix  $M$  is diagonal, and the ei-



genvalues will be found in the main diagonal of the diagonal matrix (Medvegyev, 2002, p. 454). In the principal component analysis, the coordinates of components can be calculated based on the eigenvectors of the correlation or covariance matrix, and the eigenvalues show the variances of the components. If relatively few components are needed for the eigenvalues belonging to them to account for the majority of the total variances, this suggests that the correlation values are relatively large in absolute value. If the correlation values refer to returns, the comovement of the returns can be measured with the eigenvalues which can be calculated in the principal component analysis, as, it was written by, for example, Kritzman et al. (2011).

Kritzman et al. (2011) defined the absorption ratio as the ratio of the sum of the first few eigenvalues and the sum of the total eigenvalues in an analysis which includes the covariance matrix of the asset returns. Kritzman et al. (2011) states that a larger value of the absorption ratio corresponds to a higher-level systemic risk, because the situation suggests that the sources of the risk are more uniform.

The fact that stock-market data, which would provide basis for the calculation of daily returns, are only available in the case of a few institutions would cause a problem in the calculation of the absorption ratio for the Hungarian banking and insurance data. Although daily data are not available, return values, for example the return on equity, can be calculated from accounting reports. The quantity of the return value calculated this way is, however, not sufficient to carry out the principal component analysis (the number of dates is lower than the number of variables in the database). The application of multidimensional scaling may mean a solution from a methodological point of view, in which, with certain adjustments, it is possible to carry out calculations

based on eigenvalue-eigenvector decomposition.

Multidimensional scaling is the comprehensive name of a variety of methods; one of them is metric scaling. There is a direct link between the results of principal component analysis, used in the calculation of the absorption ratio, and those of metric scaling in the case of the decomposition of the correlation matrix and the scaling of standardised Euclidean distances (Kovács, 2014, p. 226). *Bécavin et al.* (2011) also mentions that in certain cases the results of principal component analysis and multidimensional scaling may be the same. Based on this, in the following calculations we apply interval level measurement model for multidimensional scaling. Similarly to the analysis of Kritzman et al. (2011), the analysis is made on the basis of return data, and as Kritzman et al. (2011) considers the covariance matrix of returns as the starting point of the analysis, in the course of the multidimensional scaling we do not standardise the return variables. Although this was not given an important role in the analysis of Kritzman et al. (2011), in this analysis we also examined the autocorrelation of returns, and the p-value corresponding to the Box-Ljung test was generally a relatively high value in the case of first-order autocorrelations; it happened only in a few cases that the null hypothesis of the test was only acceptable at a significance level of 0.1 percent. On this basis no return data were skipped in the analysis in order to avoid any potential autocorrelation problems.

The values of the returns are calculated in the analysis as return on equity based on accounting data (the return can be calculated by dividing the value of the earnings before taxes by the value of equity). The returns were calculated in the case of institutions that published balance sheet and profit and loss statement data in each year between 2003 and 2015, and where the average return calculated on the

basis of this period was not a negative value. The data included in the analysis represent a large part of the two sectors: within the consolidated balance sheet total in 2015 the total amount of the balance sheet totals of the institutions included in the analysis represented 63.22 percent in the banking sector and 79.44 percent in the insurance sector.

The point of multidimensional scaling in this analysis situation can be summarised by saying that based on the coordinates calculable in the space with the original number of dimensions, spatial coordinates with fewer dimensions can be calculated so that the original and the 'artificial' spatial distance matrix be as similar as possible. The similarity can be measured by STRESS indicator and the  $R$ -squared indicator specific to the relation of the two types of distance values. If fitting is excellent in the space with the given number of dimensions, it is worth interpreting the multidimensional scaling spatial dimensions. In this analysis the multidimensional scaling dimensions constitute the return dimensions, and it is a really interesting research question as to what extent the banking and insurance return dimensions are similar in an excellently fitting model. The number of dimensions in the excellently fitting model is also an interesting piece of data, which can be compared to what

the number of the components (and the eigenvalues belonging to them) kept in the analysis would be in the principal component analysis.

In multidimensional scaling models one of the indicators of fitting is the STRESS (Standardised Residual Sum of Squares) indicator whose value below 0.05 refers to good fitting (Kovács, 2014, p. 228). The adequacy of fitting is also indicated by the  $R$ -squared indicator calculable concerning the relation of the two types of distance value, in which case there is no specific value for the measurement of excellent fitting; the higher the  $R$ -squared indicator, the better the alignment. The summary of the STRESS and  $R$ -squared values measured (in the case of the different numbers of dimensions) based on the data of the 16 banks and 17 insurance corporations included in the analysis is contained in *Table 1*.

From the STRESS values included in *Table 1*, it can be concluded that the 3-dimension solution in the case of the banking sector can be considered as good, while in the case of the insurance sector, the good fitting of the model can be observed for the first time in the 4-dimension solution. These results are similar to as if 3 or 4 components had been kept in a principal component analysis separately based on the 16 (banking) and 17 (insurance) variables. Of course, the number of the var-

*Table 1*

### FIT INDICATORS DEPENDING ON THE NUMBER OF DIMENSIONS

Indicators	Number of dimensions				
	1	2	3	4	5
Bank, STRESS	0.31869	0.07917	0.02933	0.01410	0.01118
Bank, $R^2$	0.82155	0.98588	0.99696	0.99921	0.99950
Insurer, STRESS	0.33831	0.13333	0.07672	0.03401	0.02092
Insurer, $R^2$	0.70510	0.90263	0.95499	0.98929	0.99533

Source: own calculation based on [www.mnb.hu](http://www.mnb.hu)

ables included in the analysis may influence the result, but the difference is relatively minor between the 16 and 17 variables, and in the insurance sector, both indicators are slightly more disadvantageous in the 4-dimension solution than in the 3-dimension solution in the banking sector (the  $R$ -squared value is lower and the STRESS value is higher). Overall, based on the results of Table 1, it can be concluded that the returns move together to a lesser extent in the insurance sector than in the banking sector, which means that the systemic risk of the insurance sector can be considered as slightly lower than that of the banking sector. The fitting indicators calculated in the two sectors can be compared in *Figures 3/a and 3/b*; these two figures also suggest the slightly lower systemic risk of the insurance sector.

Based on the results, in the case of the 16 banking return variables, the 3-dimension scaling model is well-fitting, which suggests the relatively great comovement of returns, similarly to the 4-dimension model of the insurance sector. The different types of systemic risk (cyclical and structural) may, theoretically, result in the comovement of returns; due to, for example, the asset price bubbles categorised by the MNB (2018a) into the category of cyclical systemic risk types, the returns of banks providing lending relating to real estates of similar type may change similarly to each other. Exposure concentration can be classified into the category of structural systemic risks, for example, if the lending activity of certain banks does not differ greatly in terms of customer type (MNB, 2018a), it may also result in a similar trend in the institution-level return indicators.

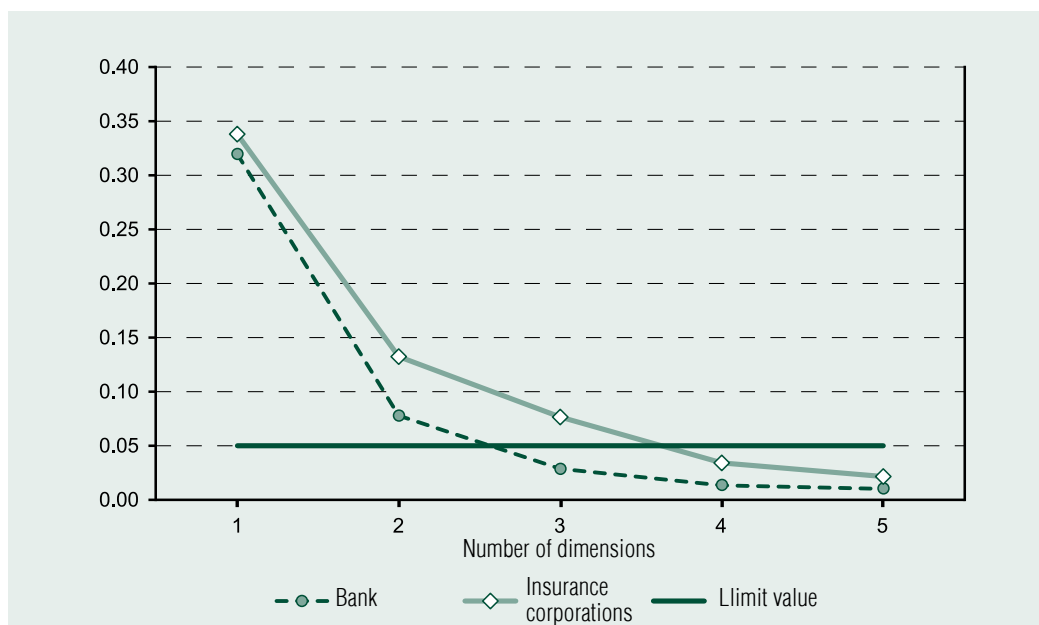
Coordinate data belonging to return dimensions are available in the well-fitting banking and insurance models, in the case of which the value of the correlation coefficient is theoretically zero, because they can correspond to the eigenvectors (similarly to the ‘artificial’ vari-

ables calculable in the principal component analysis). The (Pearson type) correlation coefficients calculable among the return dimensions of the banking and insurance sector are not necessarily zero, and their values may show the similarity of the ‘factors’ influencing the returns of the two sectors; these values of correlation coefficients are contained in *Table 2*.

In multidimensional scaling each dimension follows each other in order of ‘importance’, which means, for example, that along the first dimension, the difference of the maximum and minimum value is greater than along the second dimension. Taking this into consideration, we can state that the dimension which can be considered as the most important one in the banking sector slightly correlates with the fourth dimension in the insurance sector (and the value of the correlation cannot be considered as different from zero at a significance level of 5 percent). This result may indicate the differences of the banking and the insurance sector; based on Table 2, the dimension ‘explaining’ the banking returns the most does not have a significant influence on the returns of the insurance sector. However, the second most important dimension in the banking and the insurance sector correlates significantly. The name of this dimension (for example, based on which economic factor this dimension correlates with) could be the subject of a separate analysis, we do not discuss this issue in this analysis for reasons of space. The third dimension in the banking sector significantly correlates with the first dimension of the insurance sector, too (the sign of the correlation coefficient does not need to be interpreted in this case, because the sign of the eigenvectors belonging to the dimensions is optional), which suggests that the two sectors are similar to a certain extent. On the whole, the results suggest that the returns of the banking and the insurance sector evolve under the impact of partly different factors, and as a re-

Figure 3/a

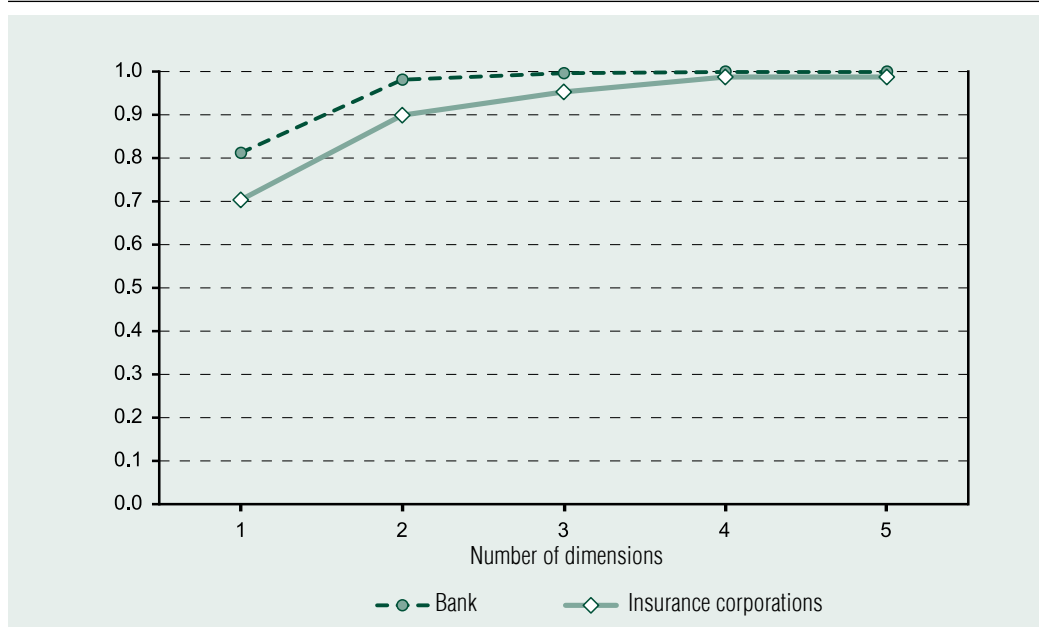
### STRESS INDICATORS DEPENDING ON THE NUMBER OF DIMENSIONS



Source: own calculations based on [www.mnb.hu](http://www.mnb.hu)

Figure 3/b

### R<sup>2</sup> INDICATORS DEPENDING ON THE NUMBER OF DIMENSIONS



Source: own calculations based on [www.mnb.hu](http://www.mnb.hu)

Table 2

**CORRELATION COEFFICIENTS IN THE CASE OF DIMENSIONS**

	Ins1	Ins2	Ins3	Ins4
Bank1	0.155	−0.143	0.451	<b>−0.537</b>
	(0.614)	(0.642)	(0.122)	<b>(0.059)</b>
Bank2	−0.306	<b>0.849</b>	0.114	0.169
	(0.310)	<b>(0.000)</b>	(0.710)	(0.581)
Bank3	<b>−0.763</b>	−0.172	−0.096	−0.342
	<b>(0.002)</b>	(0.574)	(0.754)	(0.253)

Source: own calculation based on [www.mnb.hu](http://www.mnb.hu) (p-values in brackets)

sult, there is a minor difference between the systemic risk relating to return comovement posed by the two sectors.

## SUMMARY

The systemic risk assessment relating to financial institutions have been given greater and greater attention over the last years. In this process, the operation of insurance corporations and other financial institutions in addition to banks are also given increasing attention. This study primarily would like to contribute to the literature by comparing the systemic risk of the Hungarian banking and insurance sector.

Systemic risk can be measured in a variety of ways, and in this study we discussed a method that relates to the measurement of the comovement of returns. The multidimensional scaling method used in the study is similar to the principal component analysis applied for the calculation of the indicator referred to as absorption ratio; however, it is more adequate for the analysis of the available data from a methodological point of view. No stock-market return data are available on a large part of the institutions of the Hungarian banking and

insurance sector, but returns can be calculated for each institution of the sectors from the balance sheet and profit and loss statement published annually. With a few exceptions, the study includes the return on equity data of each bank and insurance corporation between 2003 and 2015, based on which the most important return dimensions can be separated and compared across the sectors. The fit data of the solutions with different numbers of dimensions can be interpreted in a manner similar to the absorption ratio spread in the literature as a systemic risk indicator. Based on the results, it can be concluded that the systemic risk of the insurance sector relating to return comovement is slightly lower than that of the banking sector. The difference of the banking and the insurance sector is also indicted by the fact that from the return dimensions the dimension with the greatest significance in the banking sector only correlates with the dimension that is the fourth most important one for the insurance corporations. The certain degree of similarity between the two sectors is shown by the fact that the relation of the values belonging to the second dimension (second banking and insurance dimension) can be considered as significant. Overall, the results of the study are similar to the view stat-

ed in the literature that suggests that the sources of the banking and insurance systemic risk are partly different, and accordingly, the insurance systemic risk can be seen as lower than that of the banking sector.

With regard to the results, it is important to underline that the study includes a methodological approach that is similar to only one of the possible systemic risk indicators, so the conclusions might theoretically be different when the calculation of systemic risk is made by a different approach. Furthermore, it is important to note that a wide range of data is only available from the data of accounting reports in the case of Hungarian banks and in-

surance corporations, so the results cannot be directly compared with other studies which made calculations with daily returns calculated on the basis of stock exchange quotations. Having said that, the results of the study strive to describe the whole banking and insurance sector as far as possible, and as a result of the uniform methodological approach, the comparison of the two sectors is feasible. A further direction for the studies on this topic may be constituted by the definition of other return indicators from the available data, and the comparison of the results calculated by the same methodology, on the basis of different return indicators.

#### NOTE

- <sup>1</sup> The author expresses her gratitude to the reviewer for the invaluable recommendations concerning the adaption of the study.

#### REFERENCES

- ACHARYA, V. V. (2009). A Theory of Systemic Risk and Design of Prudential Bank Regulation. *Journal of Financial Stability*, 5, pp. 224–255
- ADRIAN, T., BRUNNERMEIER, M. K. (2008). Co-VaR. Federal Reserve Bank of New York Staff Reports, no. 348  
Online: [https://www.newyorkfed.org/medialibrary/media/research/staff\\_reports/sr348.pdf](https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr348.pdf)
- ARENA, M. (2008). Does Insurance Market Activity Promote Economic Growth? A Cross-Country Study for Industrialized and Developing Countries. *The Journal of Risk and Insurance*, Vol. 75, No. 4., pp. 921–946
- ARNOLD, B., BORIO, C., ELLIS, L., MOSHIRIAN, F. (2012). Systemic Risk, Macroprudential Policy Frameworks, Monitoring Financial Systems and the Evolution of Capital Adequacy. *Journal of Banking & Finance*, 36, pp. 3125–3132
- BALOG D., BÁTYI T. L., CSÓKA P., PINTÉR M. (2012). *Pénzügyi hálózatok modellezése Jackson és Watts (2002) nyomán. (The Modelling of Financial Networks Further to Jackson and Watt (2002).)* In: Egyensúly és optimum. (Equilibrium and Optimum). Tanulmányok Forgó Ferenc 70. születésnapjára. (Studies for the 70<sup>th</sup> Birthday of Ferenc Forgó). Aula Publishing House, Budapest, pp. 151–168
- DE BANDT, O., HARTMANN, P. (2000). Systemic Risk: A Survey. European Central Bank Working Paper, No. 35

- BAUR, D. G., SCHULZE, N. (2009). Financial Market Stability – A Test. *Journal of International Financial Markets, Institutions & Money*, 19, pp. 506–519
- BECK, T., WEBB, I. (2003). Economic, Demographic, and Institutional Determinants of Life Insurance Consumption Across Countries. *The World Bank Economic Review*, Vol. 17, No. 1, pp. 51–88
- BERNAL, O., GNABO, J., GUILMIN, G. (2014). Assessing the Contribution of Banks, Insurance and Other Financial Services to Systemic Risk. *Journal of Banking & Finance*, 47, pp. 270–287
- BÉCAVIN, C., TCHITCHEK, N., MINTSA-EYA, C., LESNE, A., BENECKE, A. (2011). Improving the Efficiency of Multidimensional Scaling in the Analysis of High-Dimensional Data Using Singular Value Decomposition. *Bioinformatics*, 27(10), pp. 1413–1421
- BILLIO, M., GETMANSKY, M., LO, A. W., PELIZZON, L. (2010). Measuring Systemic Risk in the Finance and Insurance Sectors. *MIT Sloan School of Management, MIT Sloan School Working Paper 4774-10*
- BILLIO, M., CAPORIN, M., PANZICA, R., PELIZZON, L. (2015). Network Connectivity and Systematic Risk. Online: [https://www.wu.ac.at/fileadmin/wu/d/i/finance/BBS-Papers/SS2015/20150303\\_Pelizzon\\_etal.pdf](https://www.wu.ac.at/fileadmin/wu/d/i/finance/BBS-Papers/SS2015/20150303_Pelizzon_etal.pdf)
- CIVITARESE, J. (2016). *Volatility and Correlation-Based Systemic Risk Measures in the US Market*. *Physica A* 459, pp. 55–67
- CHUI, A. C. W., KWOK, C. C. Y. (2008). National Culture and Life Insurance Consumption. *Journal of International Business Studies*, Vol. 39, No. 1, pp. 88–101
- Csóka P., Kiss T. (2015). Az összekapcsoltság hatása a rendszerkockázatra homogén bankrendszerben. (The Effect of Interconnectedness in a Homogeneous Banking System.) *Sigma*, 46 (1–2)
- ELING, M., PANKOKE, D. (2014). Systemic Risk in the Insurance Sector: Review and Directions for Future Research. *University of St. Gallen Working papers on finance* No. 2014/21  
Online: [http://ux-tauri.unisg.ch/publications/person/E/Martin\\_Eling/238473](http://ux-tauri.unisg.ch/publications/person/E/Martin_Eling/238473)
- ELLIS, L., HALDANE, A., MOSHIRIAN, F. (2014). Systemic Risk, Governance and Global Financial Stability. *Journal of Banking & Finance*, 45, pp. 175–181
- FÁYKISS P., SZOMBATI A. (2013). Makroprudenciális felügyelet az eurozónán kívüli európai országokban. (Macroprudential Supervision in Non-Euro Area European Countries.) *MNB Szemle különszám (MNB Bulletin Special Issue)*, pp. 63–70
- GAUTHIER, C., LEHAR, A., SOUISSI, M. (2012). Macroprudential Capital Requirements and Systemic Risk. *Journal of Financial Intermediation*, 21, pp. 594–618
- GIGLIO, S., KELLY, B., PRUITT, S. (2016). Systemic Risk and the Macroeconomy: An Empirical Evaluation. *Journal of Financial Economics*, 119, pp. 457–471
- HU, D., SCHWABE, G., LI, X. (2015). Systemic Risk Management and Investment Analysis with Financial Network Analytics: Research Opportunities and Challenges. *Financial Innovation*, 1
- HUANG, W. Q., ZHUANG, X. T., YAO, S., URYASEV, S. (2016). *A Financial Network Perspective of Financial Institutions' Systemic Risk Contributions*. *Physica A* 456, pp. 183–196
- HUANG, X., ZHOU, H., ZHU, H. (2009). A Framework for Assessing the Systemic Risk of Major Financial Institutions. *Journal of Banking & Finance*, 33, pp. 2036–2049



- KÁLMÁN, J. (2016). A pénzügyi közvetítőrendszer makroprudenciális szabályozásának és felügyeletének közigazgatási jogi aspektusai – normativitás, szervezet, eszközrendszer. (Administrative Law Aspects of the Macroprudential Regulation and Supervision of the Financial Intermediary System – Normativity, Organisation, Toolkit.) *Hitelintézet Szemle (Financial and Economic Review)*, Vol. 15 Issue 3, pp. 27–50
- KESSLER, D. (2013). Why (Re)Insurance is Not Systemic. *The Journal of Risk and Insurance*, 81(3), pp. 477–487
- KLEINOW, J., MOREIRA, F., STROBL, S., VÄHÄMAA, S. (2017). Measuring Systemic Risk: A Comparison of Alternative Market-based Approaches. *Finance Research Letters*, 21, pp. 40–46
- KOVÁCS E. (2011). A kockázat mint látens fogalom. (Risk – A Latent Concept.) *Hitelintézet Szemle (Financial and Economic Review)*, 10(4), pp. 349–359
- KOVÁCS E. (2014). *Többváltozós adatelemzés. (Multivariable Data Analysis)*. Typotex
- KRITZMAN, M., YUANZHEN, L., PAGE, S., RIGOBON, R. (2011). Principal Components as a Measure of Systemic Risk. *The Journal of Portfolio Management*, 37(4)
- LANG, J. H., IZZO, C., FAHR, S., RUZICKA, J. (2019). Anticipating the Bust: A New Cyclical Systemic Risk Indicator to Assess the Likelihood and Severity of Financial Crises. *European Central Bank Occasional Paper Series*, No. 219  
<https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op219~7483083881.en.pdf?3f125128c57998e5b8471c888c739de4>
- LUBLÓY Á. (2005). Dominóhatás a magyar bankközi piacon. (Domino Effect in the Hungarian Interbank Market.) *Közgazdasági Szemle (Economic Review)*, 59(11), pp. 377–401
- MEDVEGYEV P. (2002). *Valószínűségszámítás. (Probability Calculation.) Fejezetek a matematikai analízisből és a valószínűségszámításból. (Chapters from Mathematics Analysis and Probability Calculation.)* Aula
- MEDVEGYEV P. (2011). Néhány megjegyzés a kockázat, bizonytalanság, valószínűség kérdéséhez. (Notes on Risk, Uncertainty, Probability.) *Hitelintézet Szemle (Financial and Economic Review)*, 10(4), pp. 314–324
- MORRISON, A. D. (2003). The Economics of Capital Regulation in Financial Conglomerates. *The Geneva Papers on Risk and Insurance*, 28(3), pp. 521–533
- PAGANO, M. S., SEDUNOV, J. (2016). A Comprehensive Approach to Measuring the Relation Between Systemic Risk Exposure and Sovereign Debt. *Journal of Financial Stability*, 23, pp. 62–78
- RAFFESTIN, L. (2014). Diversification and Systemic Risk. *Journal of Banking & Finance*, 46, pp. 85–106
- SEDUNOV, J. (2016). What is the Systemic Risk Exposure of Financial Institutions? *Journal of Financial Stability*, 24, pp. 71–87
- DE SOUZA, S. R. S., SILVA, T. C., TABAK, B. M., GUERRA, S. M. (2016). Evaluating Systemic Risk Using Bank Default Probabilities in Financial Networks. *Journal of Economic Dynamics & Control*, 66, pp. 54–75
- SZEGEDI L. (2012). A pénzügyi piacok közvetlen európai felügyeletének kihívásai. (Challenges of Direct European Supervision of Financial Markets.) *Pénzügyi Szemle (Public Finance Quarterly)*. Vol. LVII Issue 3, pp. 368–379
- THIMANN, C. (2014). How Insurers Differ from Banks: A Primer on Systemic Regulation; SRC Special Paper No 3.

Online: [http://www.systemicrisk.ac.uk/sites/default/files/downloads/publications/sp-3\\_1.pdf](http://www.systemicrisk.ac.uk/sites/default/files/downloads/publications/sp-3_1.pdf)

TRICHET, J. (2005). Financial Stability and the Insurance Sector. *The Geneva Papers on Risk and Insurance*, 30, pp. 65–71

WAGNER, W. (2009). Efficient Asset Allocations in the Banking Sector and Financial Regulation. *International Journal of Central Banking*, 5(1), pp. 75–95

WEIß, G. N. F., BOSTANDZIC, D., NEUMANN, S. (2014). What Factors Drive Systemic Risk During International Financial Crises? *Journal of Banking & Finance*, 41, pp. 78–96

ECB (2017). Financial Stability Review. European Central Bank, May 2017,

Online: <https://www.ecb.europa.eu/pub/fsr/html/index.en.html>

ESRB (2015). Report on Systemic Risks in the EU Insurance Sector. European Systemic Risk Board, December 2015

MNB (2018a). Stabilitás ma – stabilitás holnap. (Stability Today – Stability Tomorrow.) A Magyar Nemzeti Bank makroprudenciális stratégiája. (The Macroprudential Strategy of the Magyar Nemzeti Bank.) Magyar Nemzeti Bank, <https://www.mnb.hu/penzugyi-stabilitas/makroprudencialis-politika/az-mnb-makroprudencialis-strategiaja>

MNB (2018b). Makroprudenciális jelentés. (Macroprudential Report.) Magyar Nemzeti Bank, <https://www.mnb.hu/kiadvanyok/jelentesek/makroprudencialis-jelentes/makroprudencialis-jelentes-2018>